ıal analysis of climate impact
sments: Handbook of Methods

ams, L. O. (2004). *Guidelines*
caling methods. Available at:
ssed on 21 December 2013.

Chapter 9

Integrated Assessment of Climate Change Impacts on Maize Farms and Farm Household Incomes in South India: A Case Study from Tamil Nadu

Paramasivam Ponnusamy[1], Geethalakshmi Vellingiri[1], Raji Reddy Danda[2], Lakshmanan Arunachalam[1], Dakshina Murthy[3], Sunandini Prema[2], Sreenivas Gade[2], Sonali P. McDermid[4], and Roberto O. Valdivia[5]

[1]*Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India*

[2]*Acharya N. G. Ranga Agricultural University, Hyderabad, Telangana, India*

[3]*International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Hyderabad, Telangana, India*

[4]*New York University, New York, NY, USA*

[5]*Oregon State University, Corvallis, OR, USA*

Introduction

South India is characterized by a wide variety of landscapes, soils and climatic zones. It is comprised of tropical, semi-arid, humid–moist, and high-altitude environments, which support a diversity of agricultural systems. Our study focuses on the state of Tamil Nadu, which is characterized by a generally tropical climate, and receives rainfall during both the southwest monsoon season (SWM, June to September) and the northeast monsoon (NEM, September to December).

Tamil Nadu has a 960-km coastline along the southernmost tip of the Indian Peninsula between 8°5’ N and 13°35’ N and 76°15’ E and 80°20’ E. Seven percent of the India’s population inhabits the state, which encompasses 4% of the land area and 3% of the water resources. Due to its proximity to the sea, Tamil Nadu experiences relatively high temperatures and humidity throughout the year. Summer

is experienced from April through June (with the temperature rising up to 40°C), and winter from November through February (with temperatures averaging 20°C). Tamil Nadu gets the major share of its rains from the NEM (48%), followed by the SWM (32%), and greater summer (15%) seasons. The average annual state-wide rainfall ranges from 535 to 2905 mm/year, with a state average annual rainfall of 945 mm.

Tamil Nadu encompasses an area of 130,058 km^2, which includes 22,934 km^2 of forest. The state has been divided into five major physiographic divisions, *viz.*, mountainous region, forest region, arid region, fertile plains, and coastal region. The Eastern and Western Ghats meet in this state and run along its east and west borders. Tamil Nadu has 3.03 million ha of cultivable land (~43% of geographical area), of which 42% is rainfed and 58% is irrigated (Department of Economics and Statistics, Tamil Nadu, 2010). Major crops grown in the state are rice, maize, sorghum, pulses, oil seeds, cotton, sugarcane, minor millets, vegetables, fruits and other horticultural crops.

Agriculture continues to be an important sector in the state economy, as more than 56% of the people depend on agriculture and allied sectors for their livelihood. Analysis of land-use patterns in Tamil Nadu reveals that in the past decade there has been a reduction in net sown area and current fallow, while the share of cultivable wastelands has increased. The area under cereals, pulses, and oilseeds had marginally declined, although area under commercial crops like turmeric, sugarcane, banana, fruits, and vegetables has shown an increasing trend. The production performance of major crops like cereals, pulses, and oilseeds has not shown any significant increase. Demand and supply gap of important crops in Tamil Nadu for the year 2010 (estimated by the State Planning Commission (Srivastava *et al.*, 2010)), indicates that the state is lagging far behind in the production of various crops.

Sixty-five percent of the Tamil Nadu's population resides in rural areas. According to National Sample Survey Organization data (1999–2000), out of the total population of 62 million in Tamil Nadu, about 12 to 17 million people are living below the poverty line. As per the poverty estimate of Rural Development Department of Government of Tamil Nadu, the overall poverty ratio stood at 22.8% in 2004 (Srivastava *et al.*, 2010).

Climate change challenges

The monsoonal rains display a large amount of internal variability and also exhibit variation with external climatic forcings, such as the El Niño Southern Oscillation (Turner and Annamalai, 2012) and the Madden–Julian Oscillation (Turner and Annamalai, 2012). In addition, there is much concern about how this already-variable system might change with climate change, and how the latter might impact coastal

agricultural communities and fisheries, which are subject to extreme storms and weather events. Regional projections suggest increased temperatures, along with increased rainfall, although much uncertainty exists in how the system's variability will change (Turner and Annamalai, 2012). Much of the region's agriculture is rainfed, and the timing of the monsoon rains is important to achieving optimal crop growth, so understanding how climate change may impact the system is critical to future agricultural planning and management. Indeed, those irrigated systems that rely on surfacewater stores are also indirectly dependent upon the monsoon rains, which supply these stores and contribute recharge to other water supplies. Water availability and use efficiency are also limited in part by fluctuations in temperature, which are further subject to change under warmer climate conditions (Mall *et al.*, 2006).

Maize-based farming system in Coimbatore, Tamil Nadu

Coimbatore is positioned at 11° N latitude and 77° E longitude with mean altitude of 426.7 m MSL. Being in the rain shadow area of Western Ghats, its climate is arid during winter (January to February), summer (March to May), and SWM (June to September) seasons. During the NEM the climate is dry subhumid as per Thornthwaite and Mather's (1955) classification. Coimbatore's annual climate is classified as semi-arid.

In Tamil Nadu, maize accounts for 83.4% (200,000 ha) of the total area. It is mainly cultivated in Perambalur, Dindigul, Coimbatore, Salem, Erode, and Virudhunagar Districts, which together share 77.1% of the total area under this crop in the state. Farmers in Tamil Nadu, who in recent years were affected by price volatility in sugarcane, turmeric, and vegetables, are now switching over to maize cultivation. Immediate liquidity in the market, store-and-sell facilities, and high demand from the poultry industry has also prompted Tamil Nadu farmers to increase the area under maize cultivation.

In Coimbatore, vegetables, maize, and groundnut are grown under garden land conditions, whereas maize, sorghum, groundnut, small millets, and pulses are grown as rainfed crops in red soils. Cotton, sorghum, bengal gram, and sunflower are raised in black soils. Farm household work, agriculture and livestock activities are complementary on a day-to-day basis. The predominant maize-based cropping systems followed in Coimbatore are, maize–sunflower/tomato, maize/maize-cotton/pulse, maize/maize, groundnut. Livestock, such as goats, cows, and poultry, are also major components in the farming systems as they play a significant role in regular employment and income generation. These activities increase the total farm income, and act as an alternative livelihood source in the event of crop failure (due to extreme weather conditions or otherwise).

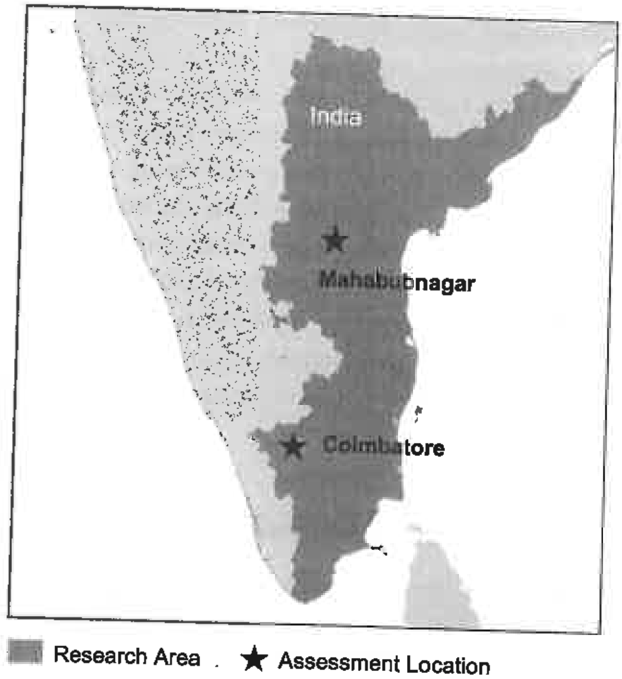


Fig. 1. AgMIP South India region, and study districts in Coimbatore, Tamil Nadu, and Mahabubnagar, Andhra Pradesh.

Representative Agricultural Pathways: Development and Interactions with Stakeholders

Climate change is now widely accepted as a significant long-term environmental challenge. Global climate and economic modelers have been developing likely scenarios of how nations might follow economic growth paths. Examples of such paths or trajectories include the representative concentration pathways (RCPs) of carbon emissions, used to inform climate model simulations, and the shared socio-economic pathways (SSPs) that describe likely future trends in biophysical and economic variables (Kriegler *et al.*, 2012; Van Vuuren *et al.*, 2011). While global SSPs may give general global projections, it is desirable to use them as guidelines to derive regional future outcomes of non-climate variables and describe them as regional SSPs. When this exercise is carried out to represent the future regional agriculture sector, they are termed regional representative agricultural pathways (RAPs). Since RAPs are statements about the likely evolution of variables like soil fertility, farm size, and regulatory policies, their development needs inputs from informed stakeholders to make them more reliable. The process of building regional RAPs is guided by the global SSPs. SSPs provide an overall future socio-economic scenario

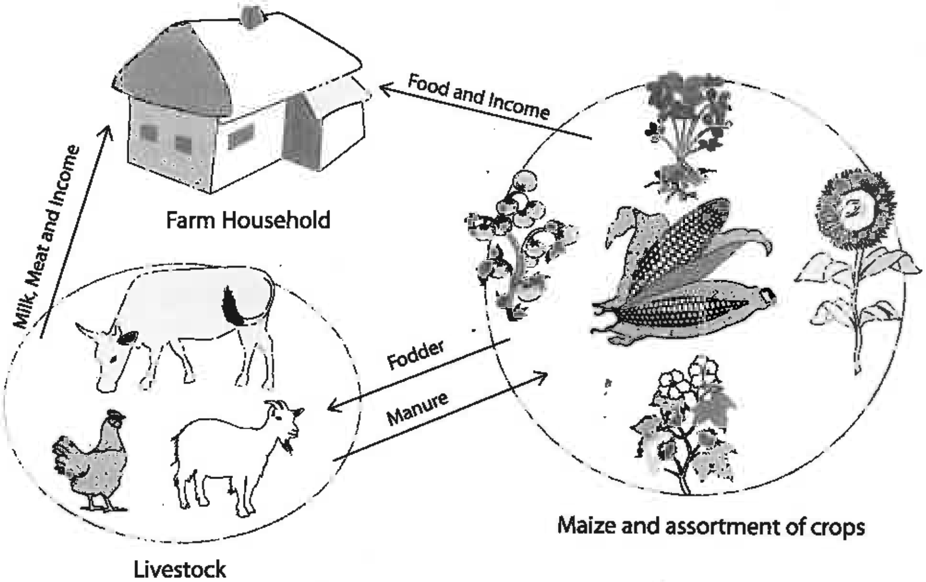


Fig. 2. Typical maize-based farming system in South India.

for the world's regions, which in turn assumes varying degrees of challenges to mitigation and adaptation strategies to climate change. SSPs and sector-specific global, national, and subnational trends guide the formulation of the regional RAPs (see Part 1, Chapter 5 in this volume).

In order to formulate these RAPs to be representative of the regional potential agricultural and socio-economic development, we sought to engage a range of stakeholders at the local, municipal, and state levels. Such a participative approach helps to characterize and integrate futuristic socio-economic productions systems with climate change impact assessment better (Berkhout *et al.*, 2002). A RAPs workshop was held on February 22, 2013 at the Department of Agricultural Economics at Tamil Nadu Agricultural University (TNAU) in Coimbatore. A brief presentation was made by the project team about the process of building RAPs so as to facilitate deeper understanding of the process and a fruitful discussion ensued. For each variable, e.g., soil quality in a particular region, the research team presented a literature-based assessment and stakeholders deliberated on how it will evolve until the end of this century. They discussed and came to a consensus on the direction of change (e.g., soil quality will decline), magnitude of change (high/medium/low), rationale for the direction and magnitude of change, specific quantitative value of change (e.g., 5% or 10%), the rationale for this particular value, and the level of agreement among the group as a whole with regard to this particular change.

A second and wider RAPs workshop that incorporated policymakers from government departments including the Planning Commission and the Department of Environment was organized on 18/19 July, 2013 by the Departments of Agricultural Economics and Agro-Climatic Research Centre at TNAU. The results of the earlier RAPs workshop and conclusions were presented to the group. The participants (the team of project scientists and the domain experts from various institutions from Tamil Nadu) deliberated on the results presented and, through intergroup discussions, arrived at a final consensus on how the socio-economic and biophysical variables pertaining to agriculture and rural development will evolve in the course of the present century.

Data and Methods of Study

The Agricultural Model Intercomparison and Improvement Project (AgMIP) integrated assessment of climate change impacts (Rosenzweig *et al.*, 2013) on agricultural production involves four components in the modeling process: Characterization of the agricultural production system, modeling climate change, simulating crop yields with crop models, and understanding how yield changes may impact the farm populations' livelihood and poverty levels. Production systems comprise crop, livestock, and other farm activities. Major crops around which the production systems are organized are identified. Calibrated and validated models for these crops are used to simulate yields under varying climate projections from climate models and management inputs derived from farm surveys. Finally adaptation options (included as part of RAPs discussions) are incorporated in crop model runs to evaluate their efficacy. The resulting yield data are used to compute crop incomes, and when combined other farm activities, can be used to compute the whole farm income. We can thus assess farm incomes for a combination of current and future production systems, with respective climate conditions and adaptation options.

Using the Tradeoff Analysis Model for Multi-dimensional Impact Assessment (TOA-MD; Antle, 2011), we can understand questions related to climate change and its impacts and the production systems better. In particular AgMIP tries to address three important issues: (1) the sensitivity of current agricultural production systems to climate change (i.e., how will the current system respond if the future climate is to be experienced now?); (2) impact of climate change on future agricultural production systems (i.e., defined by the agricultural production system as it would exist in the future and evaluate the impact of climate change); (3) the efficacy of on-farm adaptations in alleviating the impact of climate change. Three major assumptions are made to characterize the future production system, which include: There will be technological trends that will result in increased crop yields, economic trends

unrelated to climate change (as predicted by global economic models), and changes in produce prices due to global demand supply changes.

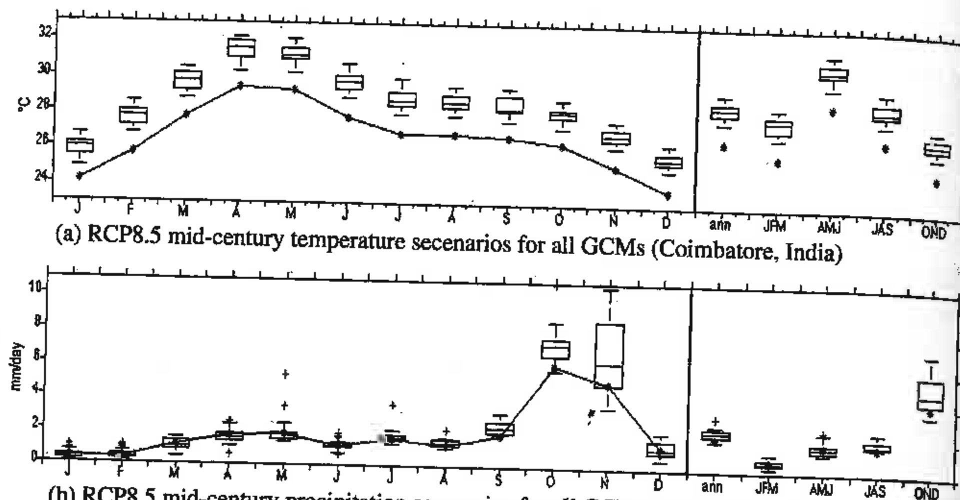
Climate data and scenarios

Baseline climate data

The study site lies in Coimbatore, which is situated in northwest Tamil Nadu, covering an area of 4889 km^2. Within Coimbatore, the analysis was focused in the Coimbatore block, which receives its maximum rainfall during the NEM season (373 mm), followed by SWM season (183 mm). The annual rainfall received is estimated to be 714 mm. The coefficients of variation (CV) are 35% and 37% for NEM and SWM rainfall, respectively. The annual average maximum and minimum temperatures in the study region are 31.8 and 21.5°C, respectively. Thirty years (1980–2010) of observed daily weather series was obtained from TNAU's Agromet observatory, located at 11° N latitude and 77° E longitude. The baseline weather datasets were quality controlled and inspected for outliers or anomalous values; if found, such values were adjusted and corrected with the AgMIP-provided AgMERRA reanalysis dataset (Ruane *et al.*, 2014). In order to create a representative 30-year weather series for each farm, we utilized neighboring sites from the highly spatially resolved WorldClim data (Hijmanss *et al.*, 2005), which is available historically as monthly values. These monthly values were used to bias-correct the existing 1980–2010 weather series for a tailored fit to each of the farm sites.

Climate projections

Projections of future climate were obtained by using the most recent Coupled Model Intercomparison Project (CMIP5) (Taylor *et al.*, 2012) and the RCPs (Moss *et al.*, 2010) for carbon emissions currently in use by the IPCC Fifth Assessment Report. Future climate projections were created by utilizing a "delta" approach, in which the mean monthly changes in important agroclimatic variables were calculated by taking the difference between the RCP8.5 climate scenario and baseline conditions. Scenarios were generated for the near term (centered around 2030), the mid-century (centered around 2055), and the end of century (centered around 2080). These monthly mean agroclimatic changes, or deltas, were then applied to the daily baseline weather series for each month. The future climate series and the corresponding projected carbon dioxide concentration from RCP8.5 were used in all crop model simulations. We refer to these future projections as "mean change scenarios". This procedure was repeated for 20 of the CMIP5 global climate models (GCMs). For the crop model and agroeconomic analyses presented in this chapter, five GCMs were selected that each represented climatic processes important in simulating the SWM and were



(a) RCP8.5 mid-century temperature secenarios for all GCMs (Coimbatore, India)

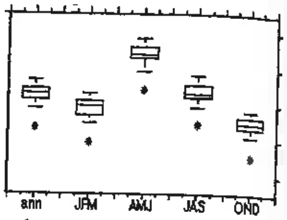
(b) RCP8.5 mid-century precipitation secenarios for all GCMs (Coimbatore, India)

Fig. 3. Projected changes in monthly mean (a) temperature and (b) rainfall for RCP8.5 mid-century in Coimbatore. Black lines and stars indicate the baseline climate and the box-and-whisker plots show the spread in projections amongst the 20 GCMs taken from CMIP5. Averages for the annual (ann), January to March (JFM), April to June (AMJ), July to September (JAS), and October to December (OND) are shown at the far right of each plot.

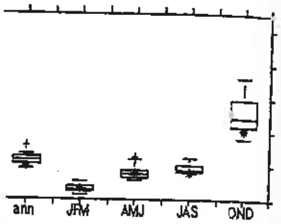
shown to adequately reproduce the regional South Asian climate. These models include CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-EMS-MR, and their selection is discussed in greater detail in Part 1, Chapter 3 in this volume.

Based on these mean change scenarios, GCMs generally showed increase in NEM rainfall in Coimbatore (Fig. 3b) although GCM typically have difficulty in simulating NEM rainfall with course resolution. However, some of the 20 GCMs also indicated declines in rainfall, and so uncertainty exists in this projection. The uncertainty is more during NEM as this season is dominated by cyclonic storm activity which might not be captured by all the models employed for NEM prediction. Rainfall during the SWM is not shown to increase substantially in Coimbatore. The GCMs do largely agree that Coimbatore will experience a significant warming throughout the year (Fig. 3a). However, there is a 2–3°C spread between the projected increases, with MIROC5 showing the smallest increase in temperature, and the HadGEM2-ES shows the greatest warming (Fig. 4). Furthermore, minimum temperature (not shown) is also projected by all the GCMs to increase, and the magnitude of increase in minimum temperature was considerably higher than the maximum temperature.

Figure 4 shows the spread of the 20 GCMs in projected temperature and rainfall over the SWM season (June to September), indicating the change from the baseline. All models show a warming, while the precipitation response is decidedly more



mbatore, India)



mbatore, India)

fall for RCP8.5 mid-century
box-and-whisker plots show
erages for the annual (ann),
, and October to December

:limate. These models
5, and MPI-EMS-MR,
apter 3 in this volume.
ly showed increase in
ally have difficulty in
some of the 20 GCMs
in this projection. The
ed by cyclonic storm
oyed for NEM predic-
ntially in Coimbatore.
e a significant warm-
C spread between the
rease in temperature,
urthermore, minimum
to increase, and the
rably higher than the

nperature and rainfall
ge from the baseline.
se is decidedly more

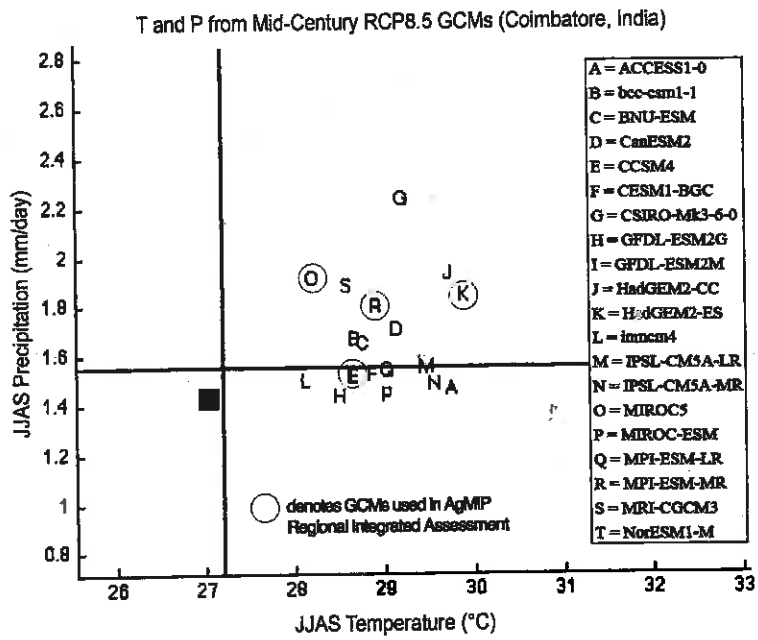


Fig. 4. Projections for SWM (June to September) rainfall and mean temperatures under RCP8.5 mid-century climate conditions in Coimbatore. Black lines indicate calculated significance thresholds (at the 0.05 level), beyond which the temperature and rainfall changes become significant. The black square indicates the baseline temperature and seasonal mean rainfall. Please refer to Part 1, Chapter 3 in this volume for more details on statistical significance testing.

uncertain. The intersecting black lines indicate the threshold of change considered significant (at the 0.05 level) for temperature and rainfall. While all temperature changes are significant, several GCMs show insignificant precipitation changes, although three of the five selected GCMs show a strongly (positive) significant rainfall response change.

Crop modeling

Crop model input data

Dynamic crop system models serve as decision supporting tools, and have been extensively utilized by agricultural scientists to evaluate the consequences from interannual climate variability and/or climate change (Challinor and Wheeler, 2008; Semenov and Doblas-Reyes 2007). Crop simulation models require quality data on climate, soil profiles, crop varieties, crop management details, etc. Efforts were made to collect long-term quality data of the study region from different sources including TNAU, a farmer survey, Department of Agriculture, and scientific experts. The details of the above parameters are discussed below.

Weather data

The weather input dataset of the DSSAT (Decision Support System for Agrotechnology Transfer) model requires the daily sum of radiation (MJ/m^{2}/day), the daily minimum and maximum air temperatures (°C), the daily precipitation (mm), windspeed (m/s), dewpoint temperature (°C), vapor pressure, and relative humidity (%). These daily weather data including site-specific information were collected from high-quality observational station data. The station data was used to create tailored weather series for all 60 farms through a bias-correction by using WorldClim monthly weather information and AgMIP climate methodologies (Part 1, Chapter 3 in this volume). These weather series were then used for creating the appropriate weather files for use with the DSSAT-maize model.

Soil information

The soil inputs describe the physical, chemical, and morphological properties of the soil surface and each soil layer within the root zone. The soil samples were collected from opened-up soil profile, and the soil physical and chemical characteristics described layer wise. The same data was used for creating the soil file (RJNR.SOL), required for running CERES-maize model. The Coimbatore district has two major soils, *viz.*, clay and sandy loam. Clay soils had a depth of up to 138 cm with drainage lower and upper limit of 0.24 and 0.44 cm^3/cm^3, bulk density of 1.14 to 1.25 g/cm^3, cation exchange capacity of 21.6 to 26.2 cmol/kgand soil organic carbon ranging from 0.48% to 0.83% in different layers. Sandy soils had depths up to 52 cm with drainage lower and upper limits of 0.13 and 0.25 cm^3/cm^3, cation exchange capacity of 9.2 to 15.9 cmol/kg, and soil organic carbon ranging from 0.48% to 0.6% in different layers.

Genetic coefficients

Plant parameters and physiological characteristics are given in the form of genotype coefficients, which describe physiological processes such as development, photosynthesis and growth for individual crop varieties. In the CERES-maize model of DSSAT, the genetic coefficients for maize are P1 (thermal time from seedling emergence to the end of the juvenile phase), P2 (extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 hours)), P5 (thermal time from silking to physiological maturity), G2 (maximum possible number of kernels per plant), G3 (kernel filling rate), and PHINT (Phylochron interval).

In the APSIM (Agricultural Production Systems Simulator) model, the coefficients calibrated for simulating maize yield include thermal times for emergence to

end of juvenile (tt_emerg_to_endjuv), flowering to maturity (tt_flower_to_maturity), flowering to start of grain (tt_flower_to_start_grain units), maximum number of grains per head (head_grain_no_max in numbers), and grain growth rate (grain_gth_rate in mg/grain/day).

Crop management data

Crop management parameters used in setting up simulations for individual farms were derived from the results of the socio-economic survey conducted in the study region. The survey captured the details on variety used, date planted, planting geometry, and fertilizer applied, etc., during the SWM season. Farmers in the study region cultivated mainly maize cultivars COH3 and COH(M)5. The crop model was calibrated for these cultivars by using the field data from experiment conducted at TNAU. Survey reports showed that the plant population normally adapted by farmers in the region varied from 60,000 to 80,000 plants/ha as per the plant geometry followed by different farmers. Survey results indicated large differences in the amount of fertilizer used by farmers. Out of 60 farmers, three had used less than 150 kg of nitrogen/ha, 30 farmers used 150–200 kg of nitrogen/ha, and 27 farmers used more than 200 kg of nitrogen/ha. While setting up of the model for individual farmers, we used the actual amounts of nitrogen fertilizer applied by them. All the farmers applied nitrogen in the form of urea via three splits, *viz.*, 25% at basal, 50% at 30 days after sowing, and 25% at flowering stage.

Model calibration

Crop simulation models APSIM and DSSAT were calibrated for maize cultivars COH3 and COH(M)5 in the study region by using the field data from experiments carried out at TNAU, Coimbatore. Date collected from six dates of sowing experiments (15.09.2000, 11.10.2000, 30.10.2000, 11.07.2001, 24.07.2001, 24.08.2001) for maize cultivar COH3 and six dates of sowing experiments (15.07.2009, 30.07.2009, 15.08.2009, 15.07.2010, 30.07.2010, 15.08.2010) for maize cultivar COH(M)5 were used for calibration of crop simulation models.

Input details required by crop simulation models (DSSAT and APSIM) including site information, soil properties, initial conditions, planting time, irrigation management (dates, amounts, and schedule), and fertilizer management (dates, amounts, sources, method of incorporation, and depth of placement) were obtained from the field experiments. The daily weather data on solar radiation, maximum and minimum air temperatures, and rainfall were collected from the TNAU observatory. CERES-maize (DSSAT) and APSIM models were calibrated by comparing simulated outcomes with the available measured data on days to tasseling, flowering, maturity, and grain yield at harvest.

The genetic coefficients that influence the occurrence of developmental stages in the crop model were derived iteratively, by manipulating the relevant coefficients to achieve the best possible match between the simulated and observed number of days to the phenological events and grain yield. Simulations with final set of parameters by both the models indicated good relationship between observed and simulated days to flowering, days to maturity, and yield (Fig. 5).

The calibrated genetic parameters of maize cultivars used in the DSSAT model are given in Table 1a. The calibrated genetic parameters of maize cultivars used in the APSIM model are given in Table 1b. The calibration efficiency has been tested by the statistical measures such as root-mean-square error (RMSE) and coefficient of determination (R^2) and the results are presented in Table 2.

The model statistics of DSSAT for COH(M)5 indicated that the R^2 values are 0.82, 0.84, and 0.85 for days to anthesis, physiological maturity, and yield, respectively, which indicate good agreement between observed and model simulated data. RMSE values for phenological stages are found to be between 2.04% and 2.12%, which indicates a good match between simulated and observed values. The RMSE for yield is found to be within the acceptable limit (351). For COH3, the R^2 value is 0.80, 0.71 and 0.73 for days to anthesis, physiological maturity, and yield, respectively, which indicates a high degree of colinearity between simulated and observed data. RMSE is less for days to anthesis and maturity (1.35 and 2.83) and yield (490), which indicates the good predicting power of the DSSAT model.

The results of the APSIM calibration for COH3 gave high R^2 values (0.65, 0.56, and 0.66 for days to anthesis, physiological maturity, and yield, respectively) and low RMSE values (2.27, 3.58, and 439 for days to anthesis, physiological maturity, and yield, respectively), which indicates good agreement between observed and simulated values. Similar results were obtained for the maize COHM5 cultivar also. The calibration efficiency was tested by using statistical measures such as RMSE and coefficient of determination (R^2) and the results are presented in Table 3.

Crop model results: Baseline analysis and future climate change impacts

Crop growth models are physiologically based, in that they calculate the relationship between various plant functions and environment. The model simulates crop behavior by predicting the growth parameters, such as biomass portioning to leaves, roots, stems, and grains. Thus, a crop growth simulation model not only predicts the final state of total biomass or harvestable yield, but also contains quantitative information

)f developmental stages in
he relevant coefficients to
. observed number of days
ith final set of parameters
. observed and simulated

sed in the DSSAT model
)f maize cultivars used in
:fficiency has been tested
· (RMSE) and coefficient
le 2.
:ated that the R^2 values
ical maturity, and yield,
served and model simu-
ıd to be between 2.04%
ted and observed values.
limit (351). For COH3,
physiological maturity.
)linearity between simu-
; and maturity (1.35 and
ıg power of the DSSAT

ɜh R^2 values (0.65, 0.56,
yield, respectively) and
;is, physiological matu-
nent between observed
e maize COHM5 culti-
atistical measures such
esults are presented in

ıange impacts

ılculate the relationship
l simulates crop behav-
tioning to leaves, roots,
t only predicts the final
uantitative information

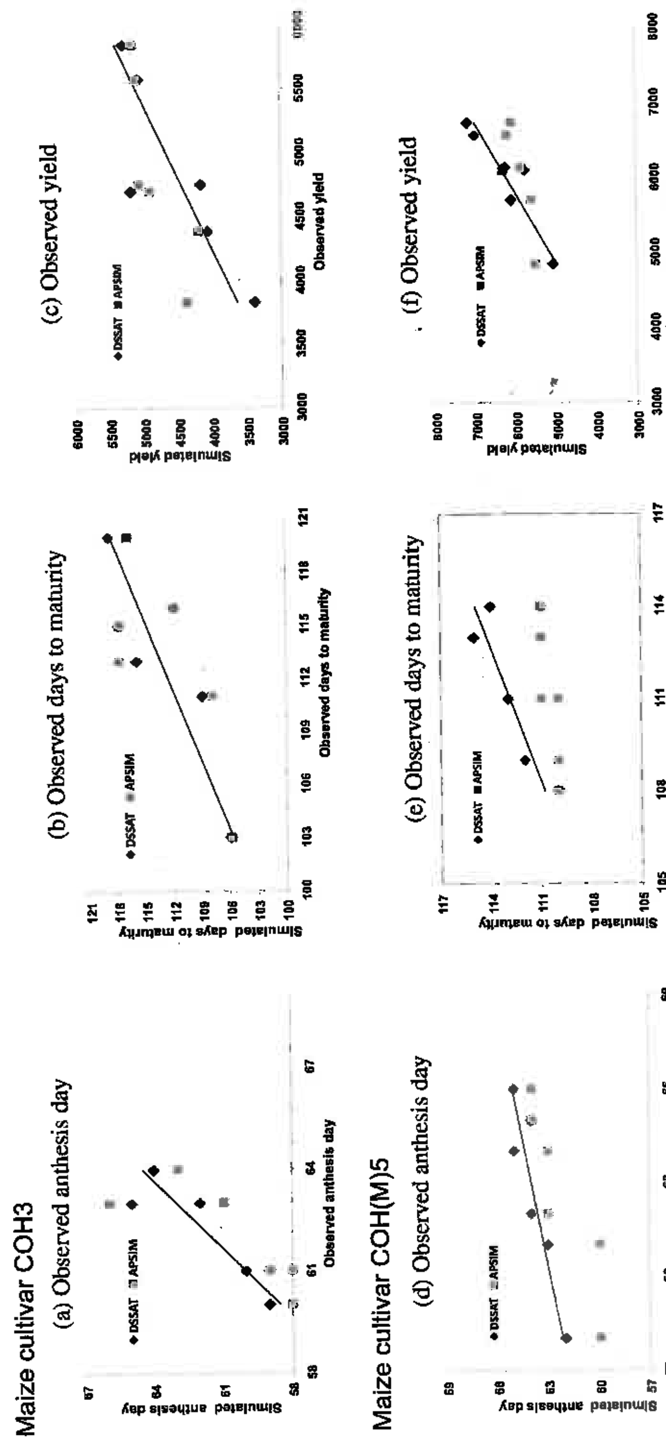


Fig. 5. (a–c) DSSAT cultivar COH3 and (d–f) APSIM cultivar COH(M)5 model predictions of days to flowering, maturity, and yield, respectively.

Table 1a. Genetic coefficients for cultivars of maize in CERES-Maize model.

Cultivar	P1	P2	P5	G2	G3	PHINT
COH3	310	0.530	900	600	7.90	38.3
COH(M)5	330	0.520	860	769	8.50	38.8

Table 1b. Genetic coefficients for maize cultivars in APSIM model.

Cultivar	tt_emerg_ to_end juv	tt_flower_ to_maturity	tt_flower_to_ start_grain units	head_grain_ no_max	grain_ gth_rate
COH3	330	845	117	793	4.6
COH(M)5	450	910	100	510	6.5

Table 2. Model statistics.

Model	Model stat.	Days to anthesis		Days to maturity		Grain yield	
		COH 3	COH(M)5	COH 3	COH(M)5	COH 3	COH(M)5
DSSAT	R^2	0.80	0.82	0.71	0.84	0.73	0.85
	RMSE	1.35	2.12	2.83	2.04	490	351
APSIM	R^2	0.65	0.81	0.56	0.64	0.66	0.64
	RMSE	2.27	1.41	3.58	1.78	439	430

Table 3. Model statistics.

Model	Model stat.	Days to anthesis	Days to maturity	Grain yield
DSSAT	R^2	0.95	0.85	348
	RMSE	0.5	0.86	0.84
	Wilmot d index	0.96	0.87	0.90
APSIM	R^2	1.1	0.4	0.93
	RMSE	0.60	1.93	277
	Wilmot d index	0.78	0.53	0.94

about major processes involved in the growth and development of a plant (Jame and Cutforth, 1996). Crop models have been used extensively to study the impact of climate change on agricultural production and food security (Hoogenboom *et al.*, 2012).

ırs of maize in

G3	PHINT
7.90	38.3
8.50	38.8

ʼs in APSIM model.

s	head_grain_no_max	grain_gth_rate
	793	4.6
	510	6.5

turity	Grain yield	
'H(M)5	COH 3	COH(M)5
).84	0.73	0.85
2.04	490	351
).64	0.66	0.64
.78	439	430

maturity	Grain yield
85	348
86	0.84
87	0.90
4	0.93
93	277
53	0.94

ɔpment of a plant (Jame and
ely to study the impact of
urity (Hoogenboom *et al.*,

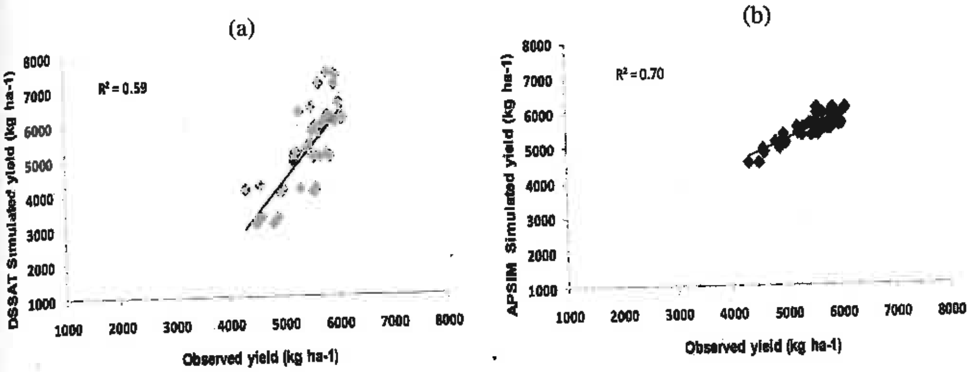


Fig. 6. Relationship between DSSAT and APSIM simulated farmers' yields and reported yields of 2010–2011 cropping season.

Calibrated DSSAT and APSIM models were forced with the survey-year weather data (2010–2011) for the 60 farmers using inputs from the farm socio-economic survey such as variety used, date planted, plant geometry, and fertilizer applied. Crop simulation model setup for the 60 farmers was done using AgMIP tools (e.g. QUAD UI). DSSAT and APSIM simulated maize crop yields for the survey year (2010–2011) were compared with the actual observed yield, and the results are depicted in Fig. 6.

Reported irrigated maize yields varied from 4317 to 6105 kg/ha during the SWM in Coimbatore. A strong correlation between simulated and reported maize yields was observed in the study region. Calibrated DSSAT and APSIM models were then forced with the historical baseline weather data (1980–2010) for 60 farmers, by taking inputs from farm socio-economic survey for the management options. The simulated grain yield is presented in Fig. 7. The results showed that there is heterogeneity among the farms baseline yield, which can be attributed to differences in sowing date, variety, amount of fertilizer applied, soil type, and other crop management practices.

DSSAT and APSIM models were then forced with future projected climate change scenarios of RCP8.5 mid-century generated from selected five GCMs for the same 60 farmers by keeping all the other model parameters constant (variety, soil, management practices, sowing time, and population) to simulate the impact of future climate on the grain yield of irrigated maize (Fig. 8).

Both DSSAT and APSIM model simulations under RCP 8.5 climate conditions (without adaptation) predicted the possibility of yield decline with varying magnitude. DSSAT simulations indicated a differential response of irrigated maize productivity to the future climate generated by different GCMs. Forcing CCSM4, MIROC5, and MPI-ESM-MR models with DSSAT showed a positive deviation in the productivity of maize by 2.33%, 22.22%, and 10.09%, respectively, while

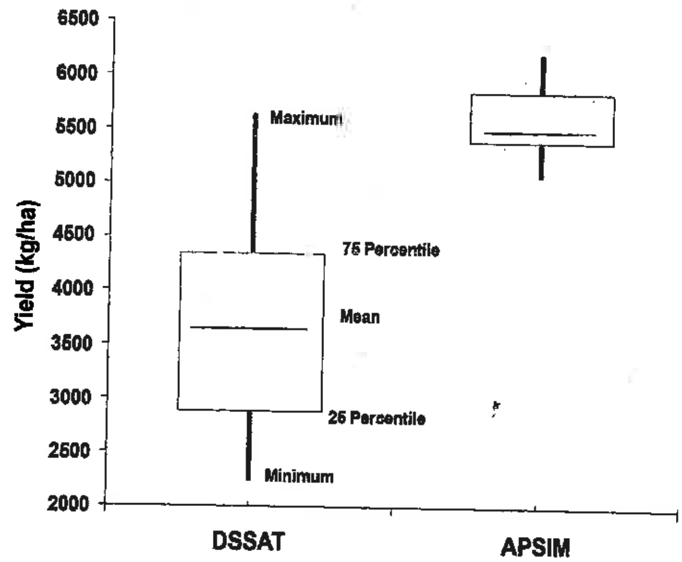


Fig. 7. Baseline DSSAT and APSIM simulated farmers' irrigated maize yields for 60 farmers in Coimbatore, India.

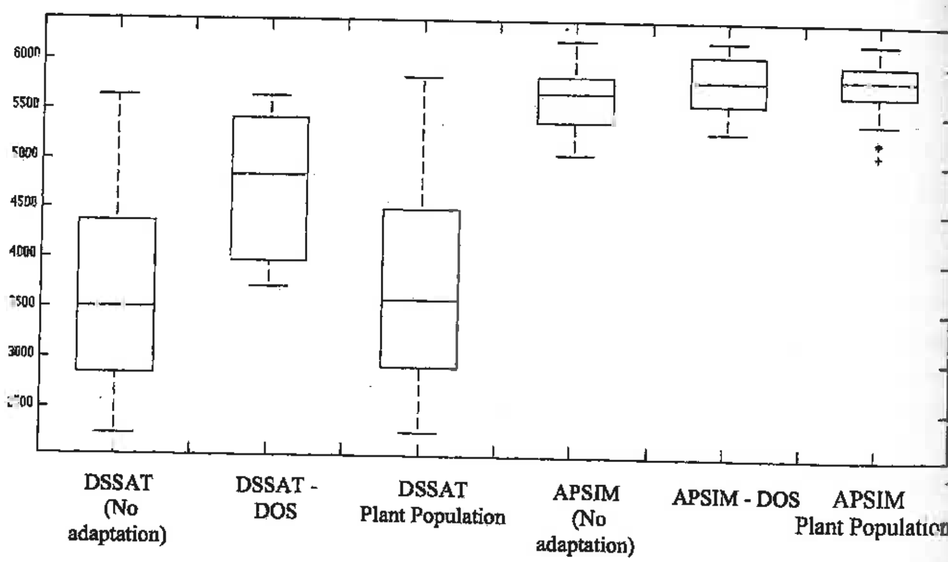


Fig. 8. Projected APSIM and DSSAT simulated maize yields for the future climate scenarios with different sowing dates (DOS) and plant populations.

GFDL-ESM2M and HadGEM2-ES model forcing projected negative deviation (–5.59% and –10.20%, respectively). In contrast, with the APSIM model, all GCM forcing projected negative deviation in irrigated maize yield ranging from –8.75% to –25.36 %. The maximum decline in yield was projected by HadGEM2-ES. DSSAT

simulation showed both positive and negative impact of climate change on maize productivity. However, the DSSAT simulated negative impact was lesser than the APSIM model as the DSSAT had more positive response for the enhanced CO_2 level in the future than APSIM. DSSAT simulation showed both positive and negative impact of climate change on maize productivity. However, the DSSAT simulated negative impact was lesser than the APSIM model as the DSSAT had more positive response for the enhanced CO_2 level in the future than APSIM.

Agroeconomic assessment

Farm survey data

Maize crop is grown under both irrigated and rainfed conditions in Coimbatore, though few maize cropped areas are purely rainfed. Maize cropped areas irrigated with groundwater are known as garden lands. Many farms that do not have surface irrigation sources drill bore wells to irrigate part of their farm holdings. The difference between rainfed maize and irrigated maize is determined by the nature of sowing. Where rainfall determines sowing the area is classified as rainfed, and where groundwater is used for sowing it is irrigated. Sometimes farmers also use "lifesaving" irrigations even if the crop is sown as rainfed.

Most farms grow some combinations of fodder sorghum, vegetables like tomato, brinjal, bhendi, groundnut, and pulses as irrigated or dry crops. Most of the farms raise an assortment of livestock including chicken, goat, sheep, buffaloes and cows, which augment farm income. Buffalos and cows are reared for milk income and goat, sheep and chicken for meat. Crop and livestock activities complement each other.

To assess and develop the variables required to undertake the integrated assessment, data collected from the ongoing Government of India Scheme on cost of cultivation of principal crops in Tamil Nadu were utilized. The data collection, organization and coding is done at the Department of Agricultural Economics, Tamil Nadu Agricultural University from where the data was obtained. Data used relate to 60 farm households that grow irrigated maize along with other crops and livestock. Maize farms are concentrated in the Tiruppur region. Summary statistics related to important variables are presented in Table 4.

Most of the households are nuclear in nature with a family size of around four. Farm sizes are also small with a holding of about 1.85 ha. Maize, other crops and livestock have each contributed almost one third of the household incomes, which indicates the relevance of interdependence. Other crops' net income, however, exhibited comparatively higher variability across farms due to the nature of crops grown and water endowments. Since there is an assortment of other crops not uniformly grown across all farms (and likewise is the case with livestock) their returns and the

Table 4. Farm survey data summary statistics.

Variables	Irrigated maize farms		
	Mean	SD	CV
Household size	4.38	1.08	24.52
Farm size	1.85	1.57	34.34
Maize area (ha)	1.00	0.30	30.16
Yld/ha	7039	996.82	14.16
Maize price/kg	10.73	1.08	10.10
Maize: gross income (Rs)	74918	24987	33.35
Maize: variable cost (Rs)	30447	8215	26.98
Maize: net income (Rs)	44471	18168	40.85
Other crops: gross (Rs)	55642	54859	98.59
Other crops: cost (Rs)	27240	30553	112.16
Other crops: net (Rs)	32152	27608	97.21
Livestock: gross (Rs)	69659	62615	89.89
Livestock: cost (Rs)	30805	62618	203.27
Livestock: net (Rs)	38854	15385	39.60
Non-farm income(Rs)	32778	24351	74.29
Gross farm income (Rs)	232996	80243	40.08
Gross cost (Rs)	88492	68006	76.85
Net farm income (Rs)	144504	35216	31.52

variable production costs associated with them are combined in monetary terms for further analytical purposes.

For this integrated assessment, maize-based farm systems under both the irrigated and rainfed systems were considered. Crop models APSIM and DSSAT were used along with management inputs from survey data to simulate yields under RCPs 4.5 and 8.5, for near, mid- and end-of-century time-periods and climate projections based on CCSM4, GFDL-ESM2M, HadGEM-2-ES, MIROC5, and MPI-ESM-MR GCMs. Simulated yields were used to calculate the current and future system parameters for economic simulations. Results for the core questions based on mid-century yield simulations are presented in subsequent sections.

RAP narrative

There will be a small increase in crop diversity due to the need to combat climate and market risks, because both of these might become more volatile in the future. Water quality and water availability for agriculture will decrease due to pollution of water bodies and competition for water from other sources. On the other hand, water use efficiency in agriculture will increase due to technological progress. Soil quality will decline by a small-to-medium extent, due to pollution and intensive cultivation caused by shrinking land base for agriculture. Most subsidies are likely

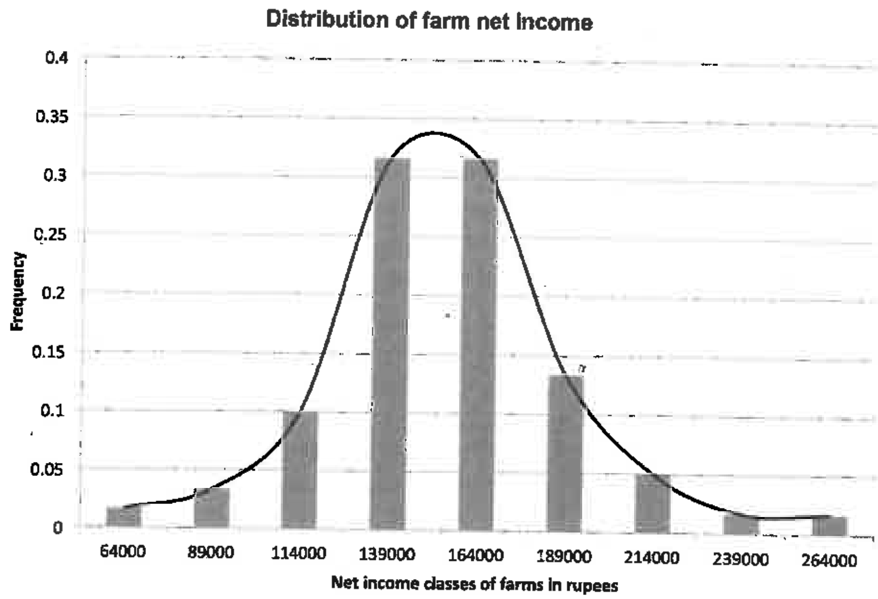


Fig. 9. Farm net income distribution for current irrigated maize production system.

to decline, while prices of agricultural commodities will increase. Farm size and wage rates will increase. Mechanization and energy use intensity will increase. The share of agriculture in overall economy will decrease, while inequality will increase. Significant decline in poverty will be associated with decrease in family size and increase in non-farm income. There will not be significant changes in food imports, while yields of important crops will increase due to technological progress in agriculture. Fertilizer use intensity and fertilizer productivity will increase. The corporate role in agriculture will increase with expanded effectiveness of commodity groups.

While the general regional RAPs cover a wide spectrum of anticipated changes of the agricultural sector in Tamil Nadu, the general consensus was that there will be shortages of land, labor, and water resources available to the sector. In particular, water is found to be the most limiting factor, followed by labor. Capital may have to substitute these factors in the form of improved technology. Thus, some of the major adaptation options identified for coping with both climate change and evolving socio-economic trends include identifying waste management techniques, improvements in land productivity by nutrient management, and improvements in cropping practices.

Tamil Nadu RAP key points include:

- Shrinking land base for agriculture
- Increased farm size and labor costs

- Increased yields of important crops
- Decreased water quality and availability
- Increased water use efficiency — technological progress
- Decline in soil quality
- Fertilizer use and fertilizer productivity increase
- Mechanization and energy use increase
- Increased commodities prices
- Decrease in subsidies
- Climate and market risks

Adaptation package

Adaptation methods enable individuals or communities to cope with or adjust to the impacts of climate change, and take advantage of potential opportunities that may result. Such strategies will include the adoption of efficient environmental-resources-management practices (e.g. the selection of a suitable planting date).

In constructing an adaptation package, it is useful to visualize the different components of the system likely to be impacted. The components of the adaptation package components can be simulated through crop models, or projected based on discussions with experts and literature review, and implemented through the TOA-MD. The process of developing RAPs further informed the adaptation package. Water shortages are envisaged to be a major limiting factor for future agriculture. The study region is partly dependent on groundwater for crop production; its shortage will be felt more and more in the future along with climate impacts. In light of this, the adaptation package envisaged includes altered sowing dates and the use of water-saving measures through drip irrigation, which does not affect the quantum of water normally available to a maize crop. Water saved is expected to be used for other crops and improving yield of fodder sorghum, which can contribute to increased returns from other crops and livestock.

Maize yield impacts due to changes in the date of sowing (DOS) component of the adaptation package were simulated by using the crop models. Other components of the adaptation package along with simulated maize yields were incorporated into TOA-MD for whole-farm analysis. Water-saving measures may involve an additional amortized cost (of an investment of about Rs. 100,000 at 8% interest for a water-saving system with a life-span of about five years) of Rs. 25,000 per hectare per year for the maize crop. This cost is included as a variable cost of maize along with area under maize crop in calculating per farm maize income contribution to the system income. Part of the saved water may be utilized for other crops, which would increase returns from other crop activities by 10%. Improved fodder availability is expected to increase livestock gross returns by 10% with an additional expenditure of 5% towards management.

ess

to cope with or adjust to
›tential opportunities that
' efficient environmental-
ıitable planting date).
sualize the different com-
onents of the adaptation
ːls, or projected based on
ıented through the TOA-
the adaptation package.
or for future agriculture.
:op production; its short-
mate impacts. In light of
/ing dates and the use of
; not affect the quantum
is expected to be used
vhich can contribute to

ɪg (DOS) component of
dels. Other components
ːlds were incorporated
ısures may involve an
),000 at 8% interest for
`Rs. 25,000 per hectare
ıle cost of maize along
›me contribution to the
ıer crops, which would
l fodder availability is
ıdditional expenditure

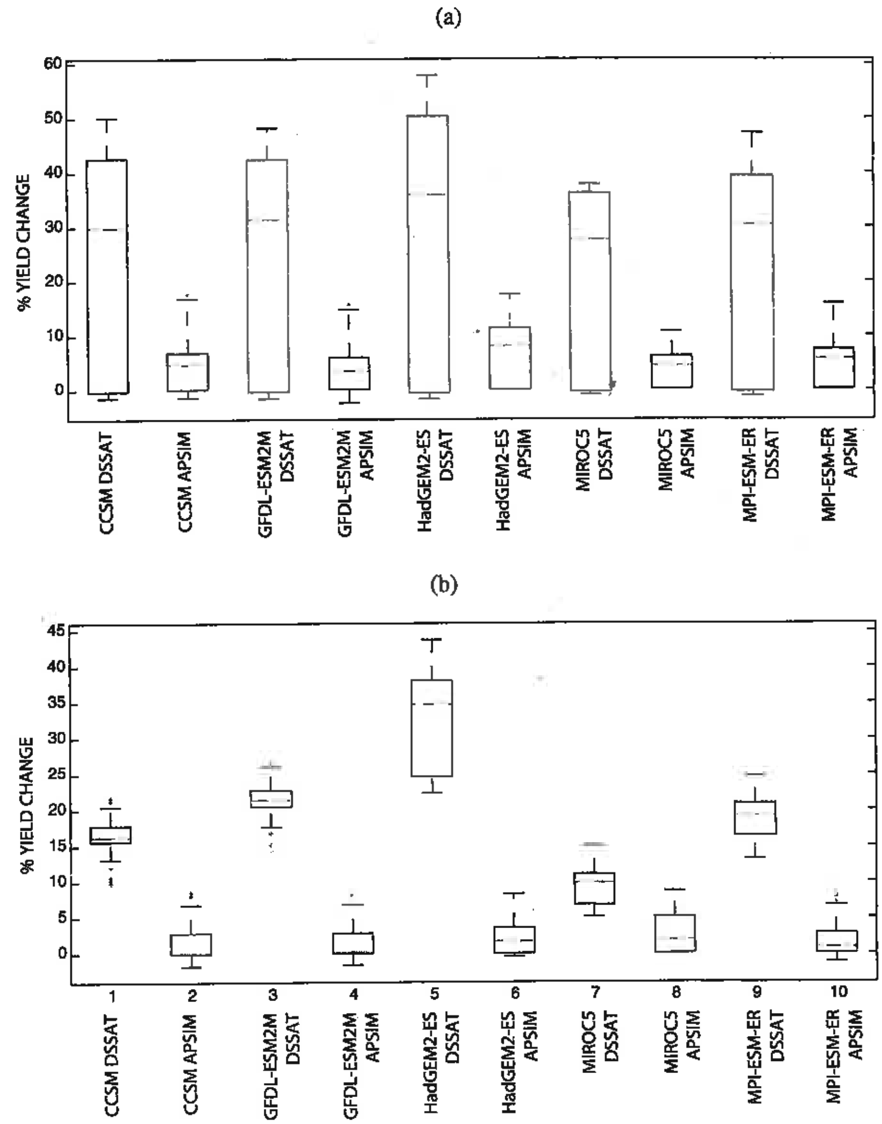


Fig. 10. (a) Percentage yield change under RCP8.5 mid-century climate conditions, with altered DOS, (b) percent yield change under RCP8.5 mid-century climate conditions with altered plant population.

Both APSIM and DSSAT crop simulation models were forced with the future climate projections of five selected GCMs (CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5 and MPI-ESM-MR) and the results are presented in Fig. 10 DSSAT and APSIM simulated maize crop yields under RCP8.5 mid-century conditions with changed DOS to be earlier and irrigation infrastructure showed that the crop yields would significantly increase compared to existing DOS practices in the future.

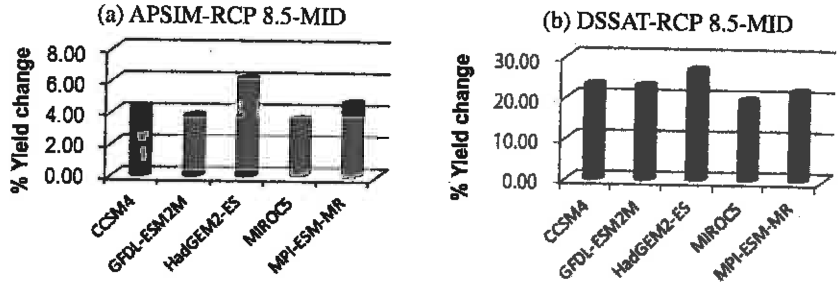


Fig. 11. DSSAT and APSIM projected changes in maize grain yields with DOS adaptation compared to climate-impacted future yields without adaptation in Coimbatore.

Adaptation options such as altering the sowing window and changing the plant population reduced the impact of climate change on maize productivity and increased maize yields relative to baseline conditions. The results indicated that, even in the future climate scenarios, a normal sowing window would increase grain yields. All the climate models projected positive yield deviations, which ranged from 14.82% to 18.37% in DSSAT and 3.38% to 5.55% in APSIM. Increasing plant population to eight plants per square meter also increased yield. The yield deviation ranged from 8.23% to 23.69% in DSSAT and 2.03% to 2.54 % in APSIM (Fig. 11).

Farm income impacts of the adaptation package were simulated using TOA-MD framework. The effects of other components of the adaptation package were estimated based on information from RAPs, and discussion with experts. As outlined earlier, improved water use was expected to contribute for 10% improved returns from other crops by reducing water delivery losses to maize crops through improved water delivery with an amortized irrigation infrastructure investment of Rs. 25,000 per hectare of maize crop. This was also expected to contribute for improved fodder sorghum yield, which would improve livestock income by 10% with 5% additional variable cost. These returns and costs along with returns and costs from maize crop with DOS adaptation were used in the TOA-MD model to assess the overall impact of the adaptation package on the farm households in terms of net returns, *per capita* income, and poverty levels.

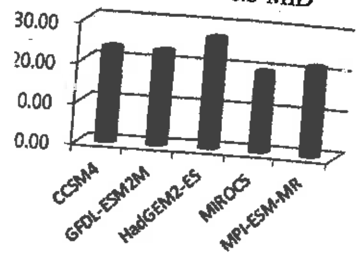
Integrated Assessment Results

In considering the impact of climate change and the adaptation package on the maize-based production system in the TOA-MD framework, we compare sets of two systems characterized by technology/climate combinations, current and future with trends, and with and without adaptations. Results of the integrated assessment for these systems are presented in this section by answering three core questions.

AgMIP protocols were used for computing climate-impacted yields, costs, and returns for maize crop (Rosenzweig *et al.*, 2013). For other activities, values were

't al.

(b) DSSAT-RCP 8.5-MID



ain yields with DOS adaptation compared
nbatore.

/ing window and changing the
lange on maize productivity and
ions. The results indicated that,
ng window would increase grain
yield deviations, which ranged
55% in APSIM. Increasing plant
eased yield. The yield deviation
to 2.54 % in APSIM (Fig. 11).
e were simulated using TOA-
f the adaptation package were
ssion with experts. As outlined
ute for 10% improved returns
naize crops through improved
ture investment of Rs. 25,000
ontribute for improved fodder
e by 10% with 5% additional
ns and costs from maize crop
l to assess the overall impact
ms of net returns, *per capita*

adaptation package on the
work, we compare sets of
nations, current and future
the integrated assessment
ing three core questions.
npacted yields, costs, and
ler activities, values were

projected depending on the three questions outlined above (climate sensitivity, climate impact, and adaptation impact) and the system addressed based on RAP information. In our integrated analysis results presented in the following sections, references to APSIM-, DSSAT-, and GCM-related farm returns, *per capita* income, and poverty rates are to be understood as relating to the whole farm TOA-MD results that used projections from the crop model/GCM combinations as TOA-MD inputs.

To test the impact of the adaptation package, maize yields under the DOS adaptation component, a "relative yield" parameter was estimated by dividing the simulated future yields with DOS by the simulated future yields without DOS (but with climate change). These yield estimates were used to derive relevant per farm revenue, cost and return variables for maize.

Core Question 1: What Is the Sensitivity of Current Agricultural Production Systems to Climate Change?

This addresses the issue of how the present production system would respond if the future climate scenario unfolds as it is at present (see Table 5 and Fig. 12). Currently existing (System 1) returns are characterized by actual farm returns based on survey data. Returns for the current system under climate change (System 2) were calculated using the relative maize yields (ratio of climate-impacted yield projections to baseline values), as described by AgMIP protocols (Rosenzweig *et al.*, 2013). Variable costs were also estimated for System 2 as per AgMIP protocols. For crops to which no crop models were applied, climate-impacted farm incomes were computed with respect to literature suggestions (e.g., Kriegler *et al.*, 2012). Different impacts of yields and prices are perceived for vegetable, pulse, groundnut, and sorghum crops when they are subjected to climate changes. A 10% negative gross income impacts for the farms with proportional changes in costs and net returns per farm. Livestock incomes of farms were also subjected to 5% negative income impacts per farm with proportional cost and net income changes. Literature (e.g., Rowlinson, 2008; Singh *et al.*, 2012) suggests that milk yields, feed uptake, and conversion efficiencies would be negatively impacted by climate change.

Simulated relative maize yields (which are the ratios between simulated and current yields) were less than one with APSIM-based estimates under an irrigated maize system across all GCMs, which indicates declines in yield. DSSAT projections presented mixed results with GFDL-ESM2M and HadGEM2-ES projecting negative yield impacts of 3.99% and 8.57%, respectively, and the other GCMs projecting varying positive impacts. MIROC5-based DSSAT projected a high 31% positive impact. Generally, across all GCMs APSIM projected higher negative yield impacts than DSSAT. When these maize yield impacts were analyzed together with other farm activities, in TOA-MD for whole farms, the "losers" (i.e. those whose farm income are negatively affected by CC) were in the range 87.67% to 91.75% except

Table 5. Sensitivity of current irrigated maize production system in Tamil Nadu to climate change.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Observed mean yield (maize kg/ha)	7039	7039	7039	7039	7039	7039	7039	7039	7039	7039
Mean yield change (maize) (%)	−14.16	3.72	−15.60	−3.99	−20.25	−8.57	−8.02	31.00	−15.17	12.90
Losers (%)	87.67	71.41	88.71	78.99	91.75	82.99	82.98	44.90	88.43	62.02
Gains (% mean net returns)/farm	6.04	8.53	5.88	7.38	5.37	6.80	6.72	13.71	5.92	10.08
Losses (% mean net returns)/farm	−16.99	−14.24	−17.28	−15.27	−18.30	−16.01	−15.81	−12.20	−17.20	−13.31
Net returns without climate change (INR)/farm	110966	110966	110966	110966	110966	110966	110966	110966	110966	110966
Net returns with climate change (INR)/farm	95288	102394	94713	99317	92852	97524	97691	113272	94877	106060
Per capita income without climate change (INR)/farm	34791	34791	34791	34791	34791	34791	34791	34794	34791	34792
Per capita income with climate change (INR)/farm	30997	32717	30858	31972	30407	31538	31578	35350	30897	33604
Poverty rate without climate change (%)	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45	34.45
Poverty rate with climate change (%)	46.20	41.42	46.61	43.42	47.96	44.64	44.51	35.11	46.49	39.16

60 INR = 1 US\$, poverty line = 1.25 US\$/person/day.

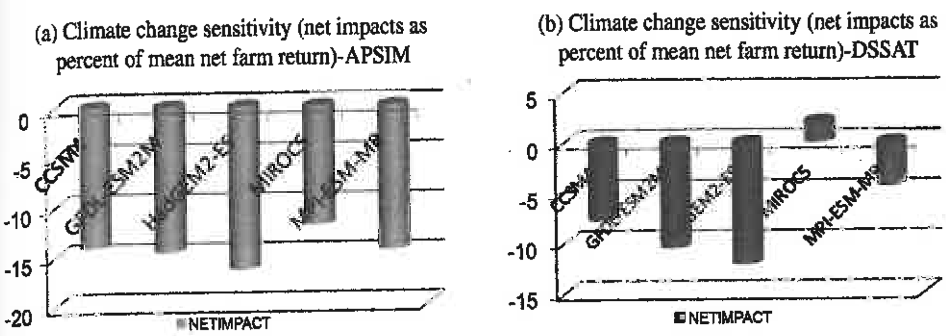


Fig. 12. Sensitivity of the current irrigated maize production system in Tamil Nadu to climate change.

for MIROC5 where it was 82.98% in the APSIM simulations. Losers were less in MIROC5, at 44.9% in the DSSAT simulation. Gains to the production system in APSIM ranged from 5.37% to 6.72% and 6.80% to 13.71% for DSSAT. APSIM projected overall negative impacts that ranged from 9.09% to 12.94%, whereas DSSAT projected similar but lower negative net impacts that ranged from 3.23% to 9.21% across different GCMs, except for MIROC5, with which DSSAT projected a positive impact of 1.51%. Simulated net farm returns, *per capita* incomes, declined across all five GCMs for APSIM and DSSAT farms except in MIROC5 for DSSAT, in-line with crop yield simulations. Poverty rates across farms thereby increased across all GCMs for APSIM and DSSAT.

In general, all APSIM simulations relating to Core Question 1 consistently indicated lower yields under climate change, lower mean net returns, lower *per capita* income, and higher poverty levels for System 2 on irrigated maize-based farms. DSSAT results projected positive impacts. The results were fairly consistent across GCMs between APSIM and DSSAT. Maize crop yield as such is sensitive to the crop model used to predict yields, followed by climate projections represented by the GCMs. At the farm level, other system activities influence the sensitivity of the whole system to climate change.

Core Question 2: What Is the Impact of Climate Change on Future Agricultural Production Systems?

This question addresses the issue of how the present production system would evolve into the future without climate change and how that future system would respond to climate change as projected by different GCMs (see Table 6 and Fig. 13). It is a difficult proposition to project future production systems, and we have approached this as a two-part exercise. Maize yields, which were simulated using crop models for the future system without climate change, were projected by using trends from global economic model projections. Other components of the system including other

Table 6. Impact of climate change on future irrigated maize production system in Tamil Nadu.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Projected mean yield (maize kg/ha)	13867	13867	13867	13867	13867	13867	13867	13867	13867	13867
Mean yield change (maize) (%)	−14.16	3.72	−15.60	−3.99	−20.25	−8.57	−8.02	31.00	−15.17	12.90
Losers (%)	93.52	57.22	94.70	77.50	97.25	86.44	85.80	11.41	94.38	34.12
Gains (% mean net returns)/farm	4.14	7.49	4.02	5.57	3.73	4.80	4.84	20.46	4.05	10.88
Losses (% mean net returns)/farm	−15.67	−8.84	−16.49	−11.02	−19.33	−12.84	−12.61	−7.00	−16.26	−7.50
Net returns without climate change (INR)/farm	238647	238647	238647	238647	238647	238647	238647	238647	238647	238647
Net returns with climate change (INR)/farm	204311	234221	201880	221260	194049	213710	214468	279980	202580	249643
Per capita income without climate change (INR)/farm	91685	91685	91685	91685	91685	91685	91685	91708	91685	91685
Per capita income with climate change (INR)/farm	80621	90259	79837	86082	77314	83649	83894	105003	80063	95228
Poverty rate without climate change (%)	2.74	2.74	2.74	2.74	2.74	2.74	2.74	2.73	2.74	2.74
Poverty rate with climate change (%)	4.19	3.41	4.28	3.73	4.58	3.98	3.76	2.69	4.24	3.11

60 INR = 1 US$, poverty line = 1.25 US$/person/day.

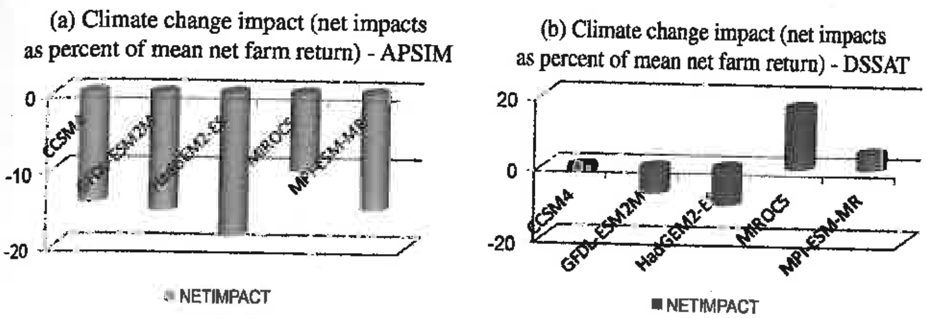


Fig. 13. Impact of climate change on future irrigated maize production system in Tamil Nadu.

crops and livestock incomes, costs, and returns were projected by using information derived from the RAPs and relevant literature.

To compute future system maize yields, present farm yields were adjusted by multiplying with autonomous yield growth trends obtained from global IMPACT model projections using the reference scenario with no climate change for maize yields in the Cauveri basin of India, which projects yields for the period from 2005–2050. As per IMPACT model projections, a factor of 1.97 was used to multiply the present yields to the future without climate change. Similarly an adjustment factor of 1.4 was used to scale producer prices for the maize produce in computing the returns. The variable cost of maize cultivation was also scaled up by 1.97.

Besides maize yields per hectare, incomes and costs of non-modeled activities of the system were modified as derived from the RAPs. Future farm size is expected to increase by 25%, family sizes are expected to become smaller by 25%, non-farm income is expected to rise by 40%, and incomes and costs from other crop activities are expected to rise in line with improving technology and together contribute for an increase of 20% gross income. Variable costs of other crops are expected to contribute an increase of 25% to overall other crops costs. Similarly livestock contribution to system income is expected to rise by 10% due to changes in composition and incomes and costs are expected to rise proportionally.

Changes in maize yields and other variables are likely to occur in this projected future farm system if future climate conditions are imposed on it (System 2 of Core Question 2). Likely changes in maize yields, and costs are estimated based on AgMIP protocols i.e., by using relative yields to calculate climate-impacted yields and proportionate changes in costs (AgMIP Handbook, Appendix 2). Climate-impacted future prices (trends with climate change) of maize were expected to be higher than future prices (trends without climate change) by 15% as projected by the IMPACT model. Based on the RAPs, the incomes for other crops are expected to be reduced by 10%, while costs are expected to be higher by 20% than in the

future system without climate change. Livestock income is expected to decline by 5% with proportionate changes in costs.

Relative yields of maize in the future system with climate change are the same as that in Core Question 1. APSIM projected negative impacts on crop yields for all GCMs in the range of around 14.16% to 20.25%, except for MIROC5 where the impact was less at –8.02% due to higher climate-impacted yield projections under this GCM. In the farm-system-based analysis which includes all activities there were more losers (around 94%) than gainers due to climate change (except in MIROC5-based simulations where the losers were less at 85.80%). Mean net return gains were in the range of 3.73% to 4.14% across all GCMs except MIROC5, where the gain was 4.84%. Losses in net returns were higher, in the range of 12.61% to 19.33 %, which indicates that net impact is of similar magnitude; this has contributed to reductions in observed *per capita* incomes for productions systems with climate change and also increased poverty rates.

DSSAT projected mixed yield results. Positive net impacts were observed in mean farm net returns relating to the GCMs MIROC5 and MPI-ESM-MR of 13.46% and 3.38%, respectively. Hence, reduced household poverty rates were shown when trends with climate change were compared with trends without climate change (Core Question 2, System 2 compared to Core Question 2, System 1). Results from CCSM4, GFDL-ESM2M, and HadGEM-2-ES indicated negative net impacts of 1.35%, 5.45%, and 8.04%, respectively with corresponding influences on poverty rates and net returns. In general, the maize production system seems to be susceptible to climate change impacts even with autonomous productivity trends as projected by the IMPACT model without climate change. MIROC5 and HadGEM-2-ES GCMs seem to have greater influence on the results than other GCMs. In general, climate change impact notwithstanding, future system returns are projected to be higher mainly due to improvements in yields, incomes, prices and, non-farm incomes of the system components. As such, the future system is projected to have almost double the farm net returns, with higher *per capita* incomes and poverty rates drastically reduced to less than 5%. Though future poverty rates were lower, in all simulations using inputs from different GCMs and crop models, poverty increased marginally in the range of 0.37% to 1.84% due to climate change, except in MIROC5 where there was a negligible decline of 0.05%. Climate change impacts seem to be influenced by crop models and GCMs in that order.

Core Question 3: What are the Benefits of Climate Change Adaptations?

By considering the maize yield component of the adaptation package alone, simulated through crop models, relative yields obtained were more than one which implies positive impacts of DOS adaptations on future farm yields and income

Table 7. Impact of DOS adaptation on irrigated maize system in Tamil Nadu.

Models/Economic Results	CCSM4		GFDL-ESM2M		HadGEM2-ES		MIROC5		MPI-ESM-MR	
	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT	APSIM	DSSAT
Projected mean yield without adaptation (Maize kg/ha)	11904	14346	11705	13282	11062	12660	12754	18122	11766	15612
Mean yield change (maize)(%)/ha	4.33	23.23	3.80	23.02	6.15	27.09	3.59	19.64	4.66	21.82
Adoption rate (%)	92.14	88.86	92.98	93.83	96.11	95.94	84.09	31.02	93.19	74.81
Projected net returns without adaptation (INR)/farm	204318	234233	201891	221440	194269	215511	214469	279980	202593	249643
Projected net returns with adaptation (INR)/farm	241116	272678	240112	271660	243775	278153	241114	285860	241543	273185
Projected *per capita* income without adaptation (INR)/farm	80623	90262	79841	86140	77385	84230	83894	105003	80067	95228
Projected *per capita* income with adaptation (INR)/farm	92480	102651	92157	102323	93337	104415	92480	106898	92618	102814
Projected poverty rate without adaptation (%)	4.19	3.41	4.28	3.73	4.57	3.93	3.76	2.69	4.24	3.11
Projected poverty rate with adaptation (%)	2.93	2.55	2.96	2.69	3.03	2.81	2.84	2.31	2.93	2.48

60 INR = 1 US$, poverty line = 1.25 US$/person/day.

levels from maize crops (see Table 7). When all the components of the adaptation package were considered as a whole in TOA-MD, it proved to be a beneficial option compared to climate-impacted future system with no adaptation package, as indicated by implied adoption rates of about or more than 90% in most GCMs and APSIM and DSSAT, except in MIROC5 simulations where the adoption rates were lowest both for DSSAT with a low 31.02% and APSIM with 84.09%. This is because the yield rate projected for the future system with climate change was the highest in MIROC5. APSIM simulations indicated smaller mean yields increase of 3.59% to 6.15% across the GCMs, while DSSAT projected higher improvements due to adaptation in the range of 19.64% to 27.09%. Poverty rates of households, *per capita* incomes levels, and mean farm net returns have shown similar responses when compared to climate change scenarios as per different GCMs, with and without adaptations.

Net farm returns and *per capita* income increase across all GCMs, and by using both APSIM and DSSAT, though the magnitudes of the increases differed across GCMs. MIROC5 was again associated with least increase, since the projected future yields before adaptation were the highest among the GCMs, and consequently the reductions in poverty were less. Adoption of the adaptation package has helped to increase farm returns, *per capita* income, and reduce poverty, which indicates the mitigating effects and benefits of an adaptation package to climate change. Activities other than maize also appeared to have significant effects in system returns as a whole with implications similar to maize in their influence on *per capita* incomes and poverty rates.

Conclusions and Next Steps

Comparing the current production system (as we have in Core Question 1) and future production systems (as in Core Question 2, i.e., a system with trends and no climate change), there were consistent increases in net returns and *per capita* income and reductions in poverty rates across all GCMs, and also between APSIM and DSSAT results, mainly due to projected autonomous trends in productivity and real prices over time in the business-as-usual SSP2 scenario. Both current and future systems simulations indicate that climate change, by and large, would have negative impacts. Adoption of the adaptation package is seen to produce improvements in net and *per capita* incomes and reductions in poverty. Thus, while irrigated maize production system is both sensitive and susceptible to climate change impacts, both natural trends in productivity improvements and the proposed adaptation package offer scope to reduce climate change impacts on the system.

The irrigated maize production system in Coimbatore, Tamil Nadu was considered for integrated analysis of climate change impacts on farm household

income and poverty through maize yields. Calibrated APSIM and DSSAT crop models were used to simulate maize yields by combining future climate parameters derived from RCP8.5 for the mid-century time frame under the CCSM4, GFDL-ESM2M, HadGEM2-ES, MIROC5, and MPI-ESM-MR GCMs, and management inputs were derived from economic farm surveys for the period 2008. These yields were converted into projected future farm yields that correspond to the simulations by using the random yield effect model. Global IMPACT economic model projections were used to adjust simulated future maize yields and prices to answer the key questions sought to be addressed through this research. Changes to the future system were projected based on variable values derived from the developed RAPs.

Global impact projections of maize yields for India vary across regions. For our study we have considered projections for Cauvery region of India as the basis for our maize yield projections. For the Cauvery region, the IMPACT model projects yield increases from 4.16 in 2009 to 8.21 tons/ha in 2050, with a growth ratio of 1.97. However, actual yield levels in the study region in the base period are higher, about 7.04 tons/ha. Therefore, using a growth factor of 1.97 to project future yields with trends may overestimate the future yields. Thus there is a need to compare projections from other global models in future work to give more robust projections.

Relating to Core Question 1, APSIM indicated lower yields under climate change, lower mean net returns, lower *per capita* income, and higher poverty levels for System 2, and DSSAT results projected mixed impacts. Maize crop yield is sensitive to the crop model used, followed by climate projections which are represented by the GCMs. At farm level, other system activities influence the sensitivity of the whole system to climate change.

Results of the analysis for Core Question 2 were similar to those from the earlier question in terms of trends. APSIM results in general predicted negative trends and DSSAT gave mixed trends. Future systems in general have higher net farm incomes, higher *per capita* income, and reduced poverty levels due to autonomous technological improvements as predicted by global models and RAPs. Climate change, however, impacts the future system. All GCMs and crop models increased poverty, though marginally, in the range of 0.37% to 1.84%, due to climate change.

By considering potential adaptation options in Core Question 3, an adaptation package with DOS, water saving, and livestock-improving components was considered for the irrigated maize production system of Tamil Nadu. Between APSIM and DSSAT results, there were consistent increases in net returns and *per capita* income and reductions in poverty rates across all GCMs. Thus, while the irrigated maize production system is both sensitive and susceptible to climate change impacts, both natural trends in productivity improvements and adaptations offer scope to reduce climate change impacts on the system. There is thus potential for a majority of the farms (upwards of 90%) to adopt this adaptation package to partially mitigate the negative

effects of climate change. Farms are likely to suffer due to climate change with the current or future production systems, at least marginally, in spite of future yield trends. With adaptation there are increased net farm incomes, *per capita* incomes, and reduced poverty levels that indicate that households may become better off.

The regional integrated analysis in South India can be extended in future by testing the adaptation package in both the current and future systems; using crop models for "baseline" simulations of the future systems, as the management input levels of the farms are projected to be different in the future system from current levels; and using multiple crop models to simulate yields of other system cropping activities that are as yet unsimulated.

References

Antle, J. M. (2011). Parsimonious Multidimensional Impact Assessment, *Am. J. Agric. Econ.*, **93** 1292–1311

Berkhout, F., Hertin, J., and Jordan, A. (2002). Socio-economic futures in climate change impact assessment: using scenarios as 'learning machines', *Global Environ. Change* **12**(2), 83–95.

Challinor, A. J. and Wheeler T. R. (2008). Crop yield reduction in the tropics under climate change: processes and uncertainties, *Agric. Forest Meteorol.*, **148** 343–356.

Hoogenboom, G., Jones, J. W., Wilkens, P. W., Porter, C. H., Boote, K. J., Hunt, L. A., Singh, U., Lizaso, J. L., White, J. W., Uryasev, O., Royce, F. S., Ogoshi, R., Gijsman, A. J., Tsuji, G. Y., and Koo, J (2012). *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5* [CD-ROM], University of Hawaii, Honolulu, Hawaii.

Jame Y. W and Cutforth H. W. (1996). Crop growth models for decision support systems, *Can J. Plant Sci.*, **76**(1) 9–19. D

Kriegler, E., O'Neill, B. C., Hallegatte, S., Kram, T., Lempert, R. J., Moss, R. H., and Wilbanks, T (2012). The need for and use of socio-economic scenarios for climate change analysis: A new approach based on shared socio-economic pathways, *Global Environ. Change*, **22**(4), 807–822.

Mall, R. K., Singh, R., Gupta, A., Srinivasan, G., and Rathore L. S. (2006). Impact of Climate Change on Indian Agriculture: A Review, *Clim. Change*, **78** 445–478.

Rosenzweig, C., Jones, J. W., Hatfield, J. L. Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria. G., and Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies, *Forest Agric. Meteorol.*, **170**, 166–182.

Rowlinson, P. (2008). Adapting Livestock Production Systems to Climate Change — Temperate Zones. Livestock and Global Change Conference Proceeding, May 2008, Tunisia.

Ruane, A. C., Goldberg, R. and Chryssanthacopoulos, J. (2014). Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation, *Agr. Forest Meteorol.*, 200. doi: 10.1016/j.agr.formet.2014.09.016.

Semenov, M. and Doblas-Reyes, F. J. (2007). Utility of dynamical seasonal forecasts in predicting crop yield, *Clim. Res.*, **34**, 71–81.

Singh, K. S., Meena, H. R., Kolekar, D. V., and Singh Y. P. (2012). Climate change impacts on livestock and adaptation strategies to sustain livestock production, *J. Vet. Adv.*, **2**, 407–412.

Srivastava, D. K., Shanmugam K. R., and Bhujanga Rao, C. (2010). *MDGs-based poverty reduction strategy for Tamil Nadu*, Monograph No. 6/2010, Madras School of Economics, Chenna, India

Thornthwaite, C. W. and Mather, J. R. (1955). *The water balance*, Laboratory of Climatology, Monograph No. 8, Centerton, NJ, USA.

Turner, A. G. and Annamalai, H. (2012). Climate change and the South Asian summer monsoon, *Nat. Clim. Change*, **2**, 587–595.

Van Vuuren, D. P., Riahi, K., Moss, R., Edmonds, J., Thomson, A., Nakicenovic, N., Kram, T., Berkhout, F., Swart, R., Janetos, A., Rose, S. K., and Arnell, N. (2012). A proposal for a new scenario framework to support research and assessment in different climate research communities, *Global Environ. Change*, **22**(1), 21–35.